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How Artificial Intelligence-Enabled Customer Behavior Analytics Reshapes Value Creation in E-Commerce Business Models

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ABSTRACT

On the largest e-commerce platforms, artificial intelligence is no longer a supplementary tool but the operating logic through which value is created, delivered, and captured. Marketing research has treated the personalization side of that shift; service research has treated the automation side. The business-model consequence has been left under-theorized: how the three canonical components of value creation are rewired when customer behavior analytics runs continuously in the loop. This paper builds a conceptual framework linking three tiers of AI-enabled analytics (descriptive, predictive, and generative) to three business-model components (value proposition, value delivery, and value capture). Drawing on secondary evidence from Amazon, Alibaba, Shein, and Shopee, we argue that AI-enabled analytics does not merely optimize existing offerings; it changes what value is being created, from products to continuously personalized experiences. Three governance tensions follow—transparency, privacy, and algorithmic dependence—which we read not as side effects but as constitutive of the reshaped model. The paper contributes a bridge between the marketing-analytics literature and business-model theory, together with a set of testable propositions for later empirical work.

KEYWORDS

Artificial intelligence; Customer behavior analytics; E-Commerce; Value creation; Business model innovation; Personalization

1 Introduction

Something that used to be called "the recommendation engine" is now doing heavier lifting than that name suggests. On modern e-commerce platforms, the same systems that once nudged a shopper toward a related product also set prices, allocate inventory, decide what appears in a live-stream feed, and increasingly draft the sales copy the customer sees. What holds these functions together is not any single algorithm but a shared underlying capability: continuously ingested behavioral signals, processed at scale, translated into actions that reach the customer within seconds. On the largest platforms, that capability is now standard equipment, not competitive edge.

The question this paper takes seriously is what that shift means for the business model, not just for the marketing mix. Value creation in early e-commerce was framed in terms familiar from bricks-and-mortar retail, assortment, price, and convenience, with the internet serving as a distribution channel and, later, a data source[1]. That framing is running out. When a platform can recognize a returning shopper before they log in, predict a category interest they have not yet declared, and adjust the price point of a bundled offer within the same second, we are no longer looking at a channel augmented by data. We are looking at a different way of producing value.

A substantial body of research already documents specific effects of AI in retailing and marketing. Huang and Rust have traced the layered mechanical, thinking, and feeling progression of service AI[2]; Davenport and colleagues have mapped its likely impact on the marketing function[3]; Guha et al. have proposed a taxonomy of retail applications organized by their customer-facing intensity and value-creation potential[4]. What is comparatively less developed is a business-model-level account: how the three canonical components (the value proposition, the mechanism of value delivery, and the way value is captured) are transformed when customer behavior analytics is not an add-on but the operating logic of the firm.

This paper offers such an account. Building on the AI business-model-innovation stream[5,6] and on marketing analytics research[7], we propose a conceptual framework that links three tiers of AI-enabled customer behavior analytics (descriptive, predictive, and generative) to the three components of the e-commerce business model. The framework is developed conceptually and illustrated with material from Amazon, Alibaba, Shein, and Shopee. The intention is to make the mechanisms visible enough to be tested in later empirical work, not to substitute for that work.

Two contributions follow. First, we bridge two literatures that have run in parallel: marketing analytics, which studies personalization, targeting, and behavior prediction; and business model innovation, which studies the architecture of value creation and appropriation. Second, we identify three governance tensions—transparency, privacy, and algorithmic dependence—that emerge as the analytics-driven model matures. We read these not as incidental side effects but as constitutive of the new model.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical background. Section 3 develops the conceptual framework. Section 4 traces the mechanisms through which AI-enabled analytics reshapes each business-

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model component, with two comparative tables. Section 5 discusses the tensions. Section 6 concludes.

2 Theoretical Background

2.1 AI-Enabled Customer Behavior Analytics as a Firm Capability

There is a temptation to treat AI in retail as a bundle of individual applications: a chatbot here, a recommender there, a demand-forecasting model somewhere in the warehouse. That framing misses what has actually changed. Following Mikalef et al.[8], we read AI-enabled analytics as an organizational capability, a stable configuration of data assets, models, workflows, and human judgment that a firm develops and reuses across many decision contexts. The specific applications are the visible surface. The capability is what lets a firm generate, refresh, and coordinate them.

It helps to separate that capability into three tiers. Descriptive analytics summarizes what has already happened (session paths, cart abandonment rates, cohort behavior) using clustering and dashboarding techniques familiar since the early 2010s. Predictive analytics uses supervised and reinforcement learning to anticipate what a shopper will do next: whether they will buy, when they will churn, how they will respond to a coupon. Generative analytics is the newest tier, most closely associated with large language and diffusion models. It produces the customer-facing artifact itself, whether that is the product description, the visual, the on-page copy, or the conversational reply. These tiers are not substitutes. A modern platform runs them together, at different cadences and against different decision horizons.

That capability has two features worth flagging before we go on. It is continuously refreshed, because every session updates the training set. And it is cross-functional, feeding not only marketing but pricing, inventory, and logistics. Those two features together are what make a business-model perspective necessary. When the same behavioral signal reshapes the ad a user sees, the price they are offered, and the delivery window that fulfilment commits to, we have passed out of "marketing analytics" and into something closer to a quality-value-loyalty chain running end-to-end on data.

2.2 Value Creation Logic in Digital Business Models

The business-model literature, at its most useful, has always turned on three questions[5,9]. What does the firm offer that customers value (the value proposition)? How is that offer produced and delivered (value delivery)? How does the firm capture a portion of the value it creates (value capture)? Digital platforms sharpened these questions but did not answer them. A digital marketplace can still sell a commodity at a thin margin, and a subscription service can still fail if the value proposition grows stale.

What analytics-driven AI adds to this triad is not another component but a different mode of running the components. In the traditional view, the value proposition is designed, tested, and periodically refreshed. In an analytics-driven model, the proposition is co-produced with each user's behavior in near real time, a shift that Lähteenmäki et al. describe in financial services as digitalization-enabled evolution of value creation[10], and that Åström et al. formalize as a three-phase framework for AI business model innovation[6]. Delivery is no longer merely scheduled. It is predictively orchestrated, with inventory positioned closer to expected demand hours before the order is placed[11]. Value capture, most consequentially, becomes conditional on the same behavioral data through dynamic pricing, personalized promotions, and targeted subscriptions, creating a tighter link between customer-facing AI and margin realization[4].

Perhaps the more honest reading is that these three shifts are not independent. Each reinforces the others. Better prediction of what a specific user wants improves the proposition, which produces more engagement, which produces more behavioral data, which sharpens prediction. This positive feedback loop is what gives analytics-driven e-commerce its structural advantage, and, as we will see, its structural vulnerabilities.

3 A Conceptual Framework

Figure 1 arranges the argument. Three tiers of AI-enabled customer behavior analytics feed into three components of the business model, which in turn produce three sets of outcomes; a feedback loop of behavioral data closes the system. That closure is the point of the diagram.

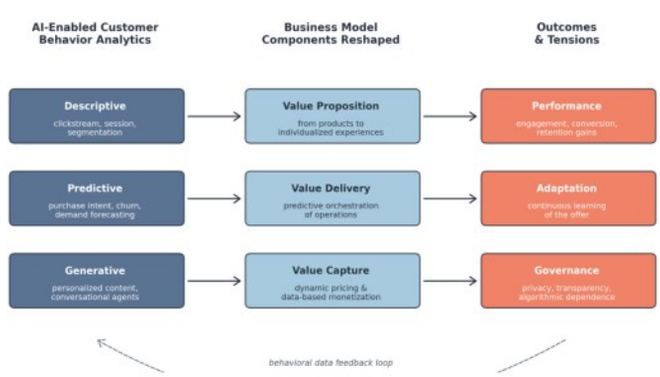


Figure 1 A conceptual framework linking AI-enabled customer behavior analytics to the components of the e-commerce business model

The framework does two things that the literature has tended to keep apart. It treats the analytics tiers not as competing techniques but as complementary layers: descriptive analytics is not obsolete because generative analytics exists; both run on the same platform, each addressing a different decision horizon. And it maps each tier to a primary but not exclusive business-model component. Descriptive analytics is most directly involved in refining the value proposition, through segmentation and behavioral profiling. Predictive analytics dominates value delivery, through demand and intent forecasting. Generative analytics increasingly shapes value capture, by producing the personalized offer that closes the sale at a price the shopper is willing to accept.

Two features of the framework matter for what follows. The outcomes column on the right is jointly positive and problematic: personalization drives engagement and conversion, but it also produces the personalization-privacy paradox now documented across a growing empirical literature[12]; predictive orchestration reduces stock-outs and delivery times, but it concentrates operational dependence on a small number of proprietary models whose failure modes are hard to audit[9]; dynamic pricing improves margin capture but raises fairness concerns whose management shapes long-run trust. And the feedback loop at the bottom of the figure is not incidental. It is what turns the framework into a dynamic rather than a static account: the outcomes observed feedback as behavioral data, which continually retrains the analytics layer, which in turn reshapes the business-model components. What we see, then, is not the AI-augmented version of a classical business model but a model that only exists in operation, with no stable equilibrium form.

4 Mechanisms Through Which AI-Enabled Analytics Reshapes Value Creation

4.1 Value Proposition: From Products to Individualized Relevance

In a pre-analytics e-commerce store, the value proposition is stated at the level of the assortment: we carry these products at these prices, in this range of styles. The customer, browsing, is expected to sort through the assortment on their own. What AI-enabled behavior analytics changes is the addressability of that proposition. Because the platform now models each shopper's latent interests, the proposition can be re-stated at the level of that shopper, in real time. The same store carries the same products. Two visitors see different homepages, different search rankings, and, with generative AI, often different product descriptions.

This is not a cosmetic shift. Empirical work on AI-driven recommendation systems reports substantial gains in engagement and conversion when systems move from rule-based to learning-based personalization[7]. Shein's fast-fashion model, for example, is often described in the business press as a supply-chain innovation, but its more distinctive feature is a very tight loop between behavioral signals (what users click on, hover over, add to cart, and abandon) and the design brief for new SKUs. Alibaba's Taobao platform similarly uses behavioral signals to construct millions of personalized landing pages in real time, most visibly during the November 11 shopping festival. In each case the value proposition is no longer "our assortment" but "the slice of our assortment that fits you today."

Table 1 Three tiers of AI-enabled customer behavior analytics and their typical e-commerce applications

Analytics tier	Primary decision task	Representative techniques	Typical e-commerce applications
Descriptive	Understand what has happened	Clustering; session/path analysis; dashboarding	Customer segmentation; cohort and funnel reports
Predictive	Anticipate what a customer will do next	Supervised learning; deep neural networks; reinforcement learning	Purchase-intent scoring; churn prediction; demand forecasting
Generative	Produce the customer-facing artifact	Large language models; diffusion models; multimodal transformers	Personalized copy and imagery; conversational sales agents

Table 1 summarizes the three tiers, their representative techniques, and typical e-commerce applications. The tiers scale with the data they consume. Descriptive analytics can run on session-level aggregates; predictive analytics needs event-level histories; generative analytics increasingly draws on multimodal data (text, images, voice) as well.

4.2 Value Delivery: Predictive Orchestration of Operations

The value-delivery component covers everything between a customer's decision to buy and the moment the product reaches them: inventory allocation, warehouse picking, last-mile routing, returns handling. Traditionally these were treated as a supply-chain problem separate from marketing. AI-enabled behavior analytics collapses that separation. When the platform predicts, three days before the customer places the order, that a particular metropolitan cluster will demand a particular SKU, it can stage inventory closer to that cluster, negotiate carrier capacity in advance, and quote a shorter delivery window, thereby increasing the probability that the order is placed at all[11].

Amazon's anticipatory-shipping patent, filed in 2013, is the most familiar instance, but the mechanism is now widespread. Alibaba's Cainiao network runs a similar logic across regional warehouses, matching forecast demand to positioned stock at a much finer geographic grain than a traditional retailer could justify. What matters for the business-model view is that the operational and marketing sides converge on the same underlying data. A predicted demand

signal is simultaneously a marketing signal worth targeting and an operations signal worth pre-staging. The business-model consequence is that operational efficiency is no longer separable from customer engagement. They are two outputs of the same analytics capability.

That convergence also introduces a specific vulnerability. Rana et al. document how AI-integrated business analytics can, under certain conditions, produce operational inefficiency rather than reduce it, particularly when models are trained on data that turn out not to represent the current environment[13]. Predictive orchestration works beautifully in stable regimes and fails ungracefully in shocks. Many platforms relearned this during the pandemic.

4.3 Value Capture: Dynamic Pricing and Monetization Pathways

Value capture in traditional e-commerce meant transaction margin plus, sometimes, advertising revenue. AI-enabled analytics multiplies the pathways. Dynamic pricing, once controversial and confined to airlines and hotels, is now standard practice on the largest platforms, with prices adjusted many times a day based on inventory levels, competitor prices, and individual-level willingness-to-pay inferred from behavior [9]. Subscription and membership revenue, Amazon Prime being the archetype, is priced and re-priced against the predicted lifetime value of the subscriber. Advertising within the platform, especially on Alibaba and Amazon, is auctioned in real time using the same behavioral profiles that power personalization. That trio of pricing, subscription, and advertising once operated as separate revenue lines. In the reshaped model they share a single behavioral input and, effectively, a single optimization loop.

Table 2 Traditional versus AI-reshaped e-commerce business model components

Component	Traditional e-commerce model	AI-reshaped model
Value proposition	Assortment stated at store level; periodic redesign; segment-level targeting	Continuously personalized offer at user level; assortment surfaced in real time
Value delivery	Post-order fulfilment scheduling; centralized inventory; batch logistics	Predictive orchestration of inventory and routing; pre-staged stock; anticipatory shipping
Value capture	Posted prices plus banner advertising; uniform promotions	Dynamic and personalized pricing; real-time ad auctions; subscriptions priced to predicted lifetime value

Table 2 sets the two side by side across the three components. Read together, the table suggests that the traditional model treats each component as a design decision made ex ante, whereas the reshaped model treats each as an ongoing computation. The design decision has not disappeared. It has moved up one level of abstraction, from designing the offer to designing the system that produces the offer.

5 Discussion: Tensions in the Reshaped Model

So far, the story has been mostly upbeat: analytics tightens the loop, the loop reshapes the model, the model performs better. Ending there would be misleading. Three tensions run through the reshaped model and shape its long-run viability.

5.1 Transparency and Accountability

Because the reshaped model is a system that produces offers rather than an offer in itself, the customer never sees the whole. They see the recommendation, not the ranking function; the price, not the pricing rule; the ad, not the auction. Grewal et al. describe this as the darkness that accompanies AI's light in retail: opacity is not a bug of individual algorithms but a feature of the system as a whole[14]. Regulatory responses, from the European Union's AI Act to sectoral consumer-protection guidance, are pushing toward explainability. The technical and organizational cost of genuine explanation at scale is high. And the literature is divided on whether it is achievable without giving up some of the personalization gains that motivated the system in the first place.

5.2 Privacy and the Behavioral-Data Loop

The engine of the reshaped model is a continuously refreshed behavioral profile. That profile is also, from a legal and normative standpoint, personal data of a peculiarly intimate kind: inferences about intent, mood, financial pressure, and so on. Empirical work on the personalization-privacy paradox consistently finds that customers value personalization when it clearly benefits them and rejects it when it does not[12]. The boundary between the two is unstable and heavily context-dependent. In our reading, firms that make the exchange feel fair, for instance by making the underlying data collection legible, appear to sustain trust; those that cannot see churn spike.

5.3 Algorithmic Dependence

A subtler tension is the firm's own dependence on the analytics system. The more the value proposition, delivery, and capture depend on continuously running models, the harder it becomes to operate, or to pivot, without them. Sjödin et al. describe this as a structural trade-off in AI-enabled business model innovation: the same models that unlock adaptive

and circular value creation also lock the firm into a particular operational logic[15]. Once a large retailer has retained its entire fulfilment stack around a specific demand model, replacing that model, or challenging its assumptions, becomes very costly. Vendor lock-in on the model side compounds the problem: much of the underlying compute and tooling is supplied by a small number of cloud providers, so the analytics capability is often only partially the firms to steer.

None of these tensions is fatal. But together they suggest that the reshaped model is not a stable end-state. It is a moving target, and part of the strategic work of running it is managing the frictions it produces.

6 Conclusions

E-commerce did not need artificial intelligence to become a data-driven industry. It was one from the start. What AI-enabled customer behavior analytics has changed is not the presence of data but the tightness of the loop between behavioral signal, business decision, and customer experience. We have argued that when the loop tightens beyond a certain point, the classical components of the business model, proposition, delivery, and capture, no longer describe an offer. They describe a continuously operating system.

The framework in Figure 1 is an initial map of that system. It sets out, deliberately at a high level, the mechanisms through which three tiers of analytics reshape the three components of value creation, and it flags three tensions (transparency, privacy, and dependence) that appear less like side effects and more like structural features. What remains for empirical work is to measure the mechanisms rigorously, to test whether the feedback loop behaves as posited, and to identify which governance approaches sustain trust as the loop tightens.

Whether that trust will hold as generative AI expands the loop further, writing not just the recommendation but the product description and, before long, negotiating the price directly with the customer, is the question this line of work keeps returning to. The framework does not resolve it. It does, we hope, sharpen the question.

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